THE BASE-RATE FALLACY IN PROBABILITY JUDGMENTS

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by

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SUMMARY

Military decision making relies heavily upon the intuitive judgments and educated guesses of decision makers and their advisors. The critical role of intuitive judgments makes it important to study the factors that limit their accuracy and to seek ways of improving these judgments. To that end, the present study examines one of the more potent errors of judgment that our research has discovered -- the base-rate fallacy.

Many situations present the decision maker with two kinds of information: <u>background</u> or <u>base-rate</u> information about how things usually are in such situations and <u>indicator</u> or <u>diagnostic</u> information telling how things appear to be in the particular situation. Unless the diagnostic information is extremely good, the usual state (base-rate) should be an important guide to judging how they are at the moment. A statistical formula, Bayes rule, tells exactly how these two kinds of information should be combined.

Failure to consider background information in situations in which it is actually very relevant is called the <u>base-rate fallacy</u>. Such failure appears to be very widespread and to affect even trained statisticians when they rely on intuition rather than calculation.

This paper tests the generality of the base-rate fallacy and examines a number of explanations for it. The examination indicates that the effect is not an artifact of how responses are elicited nor of the order in which information is presented. Nor is it due to simple misreading of the problem. It cannot be attributed to inherent inability to integrate multiple sources of

uncertainty. Base-rates are apparently ignored because subjects feel they should be ignored. In essence, base-rates often seem irrelevant when they should be given great weight. This paper suggests some problem characteristics that seem to affect the perceived relevance of base-rate information and the likelihood that it will not be ignored. One hypothesis, tested and confirmed in this study, is that base-rates will be used if they can be interpreted as relating causally to the target judgment.

In sum, this study indicates the conditions most likely to produce the base-rate fallacy. The knowledge obtained here, leading towards an understanding of when base rates are and are not viewed as relevant, has direct implications for training people to overcome this bias.

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1. INTRODUCTION

1.1 The Base-Rate Fallacy: Examples and Implications

Problem 1: Two cab companies operate in given city, the Blue and the Green (according to the color of cab they run). 85% of the cabs in the city are Blue, and the remaining 15% are Green.

> A cab was involved in a hit-and-run accident at night. A witness later identified the cab as a Green cab.

The court tested the witness' ability to distinguish between Blue and Green cabs under nighttime visibility conditions. It found the witness able to identify each color correctly about 80% of the time, but confusing it with the other color about 20% of the time. What do you think are the chances that the errant cab was indeed Green, as the witness claimed?

(following Kahneman & Tversky, 1972b)

This is a paradigmatic Bayesian inference problem. It contains two kinds of information. One is in the form of background data on the color distribution of cabs in the city. We shall call this base-rate information. The second, rendered by the witness, relates specifically to the cab in question, and we shall call this indicant or diagnostic information.

The proper, normative way to combine the inferential impacts of base-rate evidence and diagnostic evidence is given by Bayes' rule. In odds form, this rule can be written as $O = Q \cdot R$,

where 0 denotes the posterior odds in favor of a particular inference; Q denotes the prior odds in favor of that particular inference; and R denotes the likelihood ratio for that inference. In the cab example above, we are interested in the probability, after the witness' testimony, that the errant cab was Green. Denote Green cabs and Blue cabs by G and B, respectively, and denote the testimony that the cab was green by g. Spelling out Bayes' Theorem in full, we obtain:

$$O = \frac{P(G/g)}{P(B/g)} = \frac{P(g/G)}{P(g/B)} \times \frac{P(G)}{P(B)} = \frac{.8}{.2} \times \frac{.15}{.85} = \frac{12}{17}$$

and thus $P(G/g) = \frac{12}{12+17} = .41$. Note that the prior odds are based on the population base rates, whereas the likelihood ratio is determined by the indicator.

If a posterior probability of 41% seems counterintuitive to you and your initial inclination is to be 80% sure that the witness' testimony of Green is in fact reliable, then you are exhibiting the base-rate fallacy -- the fallacy of allowing indicators to dominate base rates in your probability assessments. You are, however, in good company. The base-rate fallacy has been found in several experimental studies (see Section II), and it manifests itself in a multitude of real-world situations.

In a 1955 paper, Meehl and Rosen warned against the insensitivity of both the designers of diagnostic tests and their subsequent users to base-rate considerations, and their proneness to evaluate tests by their hit rate (i.e., diagnosticity) alone, rather than by the more appropriate measure of efficiency, which would take into account base rates, as well as costs, goals, and other relevant considerations. Clinicians are apparently unaware

that they should feel less confident when a test returns a rare verdict (such as "suicidal") than when it returns a more common one.

Such warnings persist to our day. Lykken (1975) laments current injudicious use of polygraph outputs by commercial companies, while demonstrating that even a highly accurate polygraph reading is very likely to yield erroneous diagnoses when, say, it is administered to a whole population of employees, only a fraction of whom are really guilty of some offense. Dershowitz (1971), Stone (1975) and McGargee (1976) point out that since violence is a rare form of behavior in the population, base-rate considerations alone make it more likely than not that an individual who is preventively detained because he is judged to be potentially dangerous is really quite harmless, a purely statistical argument whose significance has only recently gained appreciation among jurists.

Base rates play a problematic role in yet another legal context, namely the fact-finding process. Though there is no definitive ruling on the status of base-rate evidence, courts are typically reluctant to allow its presentation often ruling it inadmissible on grounds of irrelevancy to the debated issues. While some of the legal objections reflect sound reasoning, others are clearly manifestations of the base-rate fallacy. (For a discussion of base rates in the courts, see Tribe, 1971.)

The counterpart of disregarding the probative impact of base rates lies in overjudging the probative impact of indicators. To hark to a well-known children's riddle, white sheep eat more grass than black sheep simply because there are more of them. Color is really no indicator of appetite -- the phenomenon is a base-rate one, as is the fact that in 1957 in Rhode Island more pedestrians were killed when crossing an intersection with the signal than against it (Huff, 1959). An entire methodology

of experimental control has been conceived to guard against this prevalent side effect of the base-rate fallacy.

The base-rate fallacy may underlie some phenomena noted in the domain of interpersonal perception as well. Nisbett and Borgida (1975) have used this notion to explain the perplexingly minimal role that consensus information typically plays in people's causal attributions, consensus data being, in effect, base-rate data. The consequences of the base-rate fallacy to interpersonal perception was also unwittingly demonstrated by Gage (1955). Gage found that predicting the questionnaire behavior of strangers drawn from a familiar population deteriorated following an opportunity to observe these strangers engaging in expressive behavior. If we suppose (a) that the indicators gleaned from these observations suppressed the base-rate information which was previously available through the familiarity with the source population of these strangers; and (b) that these base-rate considerations were more diagnostic (i.e., more extreme) in themselves than the expressive behavior was, then Gage's results are readily understood.

1.2 Experimental Studies Of The Base-Rate Fallacy

Although the existence of the base-rate fallacy has been acknowledged for quite some while (Meehl & Rosen, 1955; Huff, 1959; Good, 1968), it was first studied in a controlled laboratory situation by Kahneman and Tversky (1973). These investigators presented subjects with a series of short personality sketches of people randomly drawn from a population with known composition. On the basis of these sketches, subjects were to predict to which of the population subclasses the described persons were most likely to belong. Subjects were responsive to the diagnosticity

of the descriptions, but they were almost totally oblivious to the fact that the different subclasses of the population were of grossly different size. Therefore, subjects were as confident when predicting membership in a small subclass (which correspondingly enjoys a smaller prior probability) as in a larger one; Kahneman and Tversky interpreted their results as showing that:

> ... people predict by representativeness, that is, they select ... outcomes by the degree to which (they) represent the essential features of the evidence ... However, because there are factors (e.g., the prior probability of outcomes...) which affect the likelihood of outcomes but not their representativeness, ... intuitive predictions violate the statistical rules or predictions (pp. 237-238).

This interpretation explains how subjects derive judgments of diagnosticity from personality sketches, but not why these are not combined with base-rate information. That indicators tend to dominate base rates even when no judgments of representativeness are involved is evident from consideration of problem 1, with which this paper opens. An essentially identical problem was presented to a total of 147 subjects in the course of three studies (Kahneman & Tversky, 1972b; Lyon & Slovic, 1976; Bar-Hillel, Note 1). The median and modal assessments given by these subjects were 80%, compared with the correct Bayesian assessment of 41% as computed above -- a clear case of the base-rate fallacy.

Another interpretation of Kahneman and Tversky's results was offered by Nisbett, Borgida, Crandall and Reed (1975), who suggested that base-rate information is ignored in favor of target-case information, since the former is "remote, pallid

and abstract", whereas the latter is "vivid, salient and concrete". (p. 24) Problem 1 again shows the phenomenon to be more general than these authors may have realized.

Recent investigations have addressed themselves to the stability of the base-rate phenomenon (Lyon & Slovic, 1976; Bar-Hillel, Note 1). A wide range of variations of the basic problem was presented to a total of about 350 subjects. These have included (a) changing the order of data presentation with the indicator data preceding, rather than following, the base-rate information; (b) using green rather than blue as majority color; (c) having subjects assess the probability that the witness erred, rather than the probability of correct identification; (d) having the witness identify the errant cab as belonging to the larger, rather than the smaller, of the two companies; (e) varying the base rate (to 60% and 50%); (f) varying the witness' credibility (to 60% and 50% hits); and (g) stating the problem in a brief verbal description without explicit statistics (e.g., "most of the cabs in the city are Blue", and "the witness was sometimes, but rarely, mistaken in his identifications")(Kahneman & Tversky, Note 2).

Through all these variations, the median and modal responses were consistently based on the indicator alone, demonstrating the robustness of the base-rate fallacy. It seems that people ignore base rates in these problems for the simple reason that they consider them irrelevant. In fact, Lyon and Slovic (1976) presented subjects with a forced-choice question regarding the relevance of the two items of information. Subjects were offered reasoned statements in favor of (a) only base rates being relevant; (b) only the indicator being relevant, and (c) both being relevant. In spite of the fact

that the correct argument was explicitly formulated in (c), 50% of their subjects chose (b). In another study, Hammerton (1973) gave his subjects a similar kind of problem, but omitted the base rates altogether. His subjects showed no awareness that a vital ingredient was missing.

The present study views the subjective judgment of "relevancy" as a key concept for understanding the base-rate fallacy. It includes a series of problems; some were designed to rule out alternative explanations of the phenomenom; others were designed to confirm the account put forth by the author. Briefly, this account suggests that people order informational items according to their perceived relevance to the required judgment. More relevant items dominate less relevant ones. Items are combined only if they are perceived as equally relevant. (A full presentation can be found in Section VII.) Where it has been demonstrated, the base-rate fallacy is a direct result of base rates having been (subjectively) less relevant than the indicators. This study will show that by manipulating relevancy, the fallacious tendency to ignore base rates can be controlled.

2. THE STUDY

2.1 Subjects and Method

The empirical core of this paper is a collection of inference problems, like Problem 1, which were presented to about 1500 subjects in the course of the study. These subjects were predominantly Hebrew University applicants who answered the problems in the context of their university entrance exams, and thus presumably were highly motivated to do their best. Subjects usually received only one problem, but occasionally two or three. When subjects received more than one problem, these were chosen to be quite different from each other, so as to minimize interference. The total number of responses analyzed approaches 3000. Hebrew University applicants are all high school graduates, mostly 18-23 years old, and of both sexes. The remainder of our subjects were undergraduate volunteers. Subjects were not instructed to work quickly, but questionnaires were retrieved after about 4 minutes (per question), and those who had not answered by then were simply discarded. Four minutes was ample time for an overwhelming majority of the subjects.

In all, about 45 problems were employed, only seven of which will be presented in detail. The rest will be only briefly sketched.

2.2 The Cab Problem

Problem 1, with which we opened this paper, serves as a point of departure for much of the discussion of the base-rate phenomenon.

Figure 2-1 presents the distribution of estimates that 52[1] subjects gave to this problem. Thirty-six percent of these subjects based their estimate on the witness' credibility alone (.80), ignoring the base rate altogether. Eighty percent was also the median estimate. Only about 10% of the subjects gave estimates that even roughly approximated the normative Bayesian estimate of 41%.

The same pattern of results was obtained with the whole spectrum of variations described in Section II. The modal answer, which invariably matched the witness' diagnosticity, was given by up to 70% of the subjects.

There is a very seductive argument, applicable to Problem 1, which would generate the base-rate fallacy. It proceeds as follows: our witness has identified the errant cab's color; his color identifications are accurate 80% of the time; *ergo*, this particular identification has an 80% chance of being accurate.

The flaw in this argument is subtle. We happen to know *what* color attribution the witness made, and it is a minority color. Although the witness is perceptually unbiased in favor of either color, the ecology is a fact reflected in his identifications. By the formula of total probability, a randomly selected cab in that city has a 71% (.8 x .85 + .2 x .15) probability of being perceived as Blue by our witness, versus 29% for Green. Moreover, a percept of Green is more likely to be erroneously produced by a Blue cab (.85 x .2 = .17) than appropriately produced by a Green one (.8 x .15 = .12).[2]

In this figure, as in those to follow, the arrow indicates the correct Bayesian estimate; Md stands for Median; Mo stands for Mode; the number to the right of the tallest line states the frequency of the modal response.

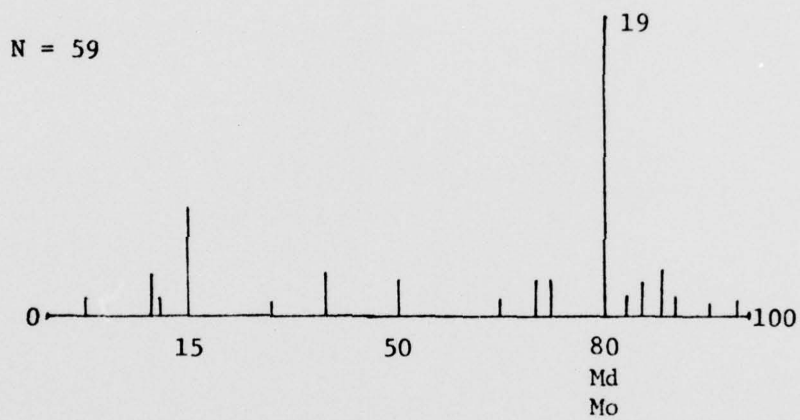

FIGURE 2-1. DISTRIBUTION OF RESPONSES TO CABPROBLEM

To return to Figure 1, it might be thought that though subjects err in falling for the above reasoning, that error is not a manifestation of the base-rate fallacy at all. Since the argument relies heavily on the presence of direct, though fallible, testimony, we could observe what happens when an indicator that does not lend itself to the same argument is substituted for the witness.

2.3 The Suicide Problem

Such an attempt is to be found in Problem 2.

> Problem 2: A study was done on causes of suicide among young adults (aged 25 to 35). It was found that the percentage of suicides is three times larger among single people than among married people. In this age group, 80% are married and 20% are single. Of 100 cases of suicide among people aged 25 to 35, how many would you estimate were single?

Formally, this problem presents the same two items of information as Problem 1. There is base-rate information regarding marital status, and diagnostic information regarding suicide rates. The diagnostic information, however, rather than applying directly to a specific target case, is itself a population property with a distribution of its own, and derives its diagnostic powers by virtue of having different base rates in the two population subclasses.

The distribution of estimates that 37 subjects gave to Problem 2 is shown in Figure 2-2. Forty-three percent of the subjects gave a response based on the likelihood ratio alone

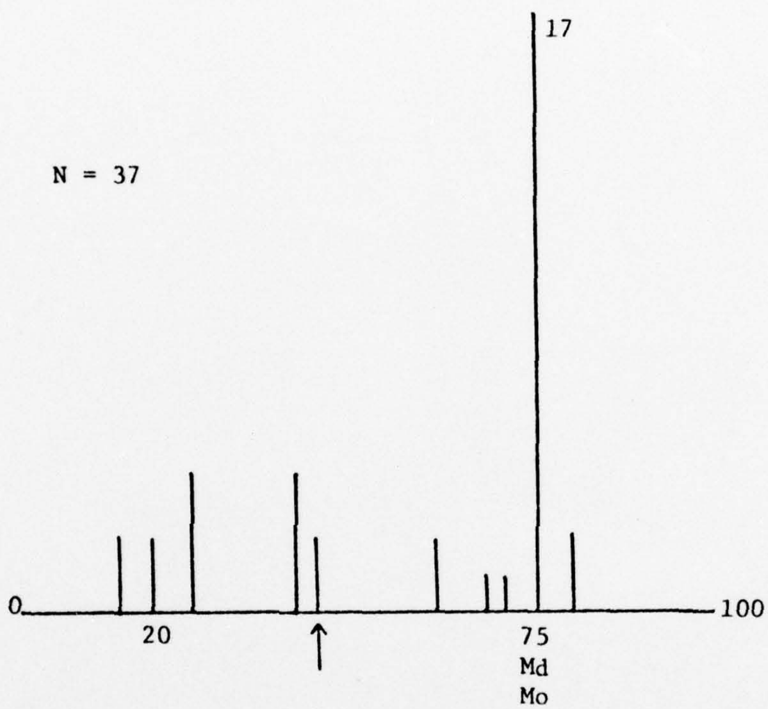

FIGURE 2-2. DISTRIBUTION OF RESPONSES TO SUICIDE PROBLEM 2

(75%), completely ignoring the fact that more young adults are married than are single. The median response was also 75%.

A Bayesian estimate based on the given data gives the answer as 43% (0 = .2/.8 x 3 = 3/4), but only six responses fell between 30% and 50%.

To test for robustness, Problem 2 was subjected to a host of variations, including (a) not mentioning the base rates explicitly within the problem (presumably all our subjects knew that a majority of adults aged 25 to 35 are married); (b) asking subjects to supply, along with their answers, estimates of the missing, but necessary, base rate (the results of these estimates confirmed the assumption in [a][3]); (c) varying the base rates (with the values 50%, 10%, and 5%); (d) varying the likelihood ratio (3 and 9); (e) providing purported "actual" suicide rates (5% and 15% of deaths) rather than just the likelihood ratios; (f) inverting the indicator to support the base-rate implication; (g) asking about the chances that an individual suicide was single, rather than for the number of singles among 100 suicides; and (h) changing the cover story to deal with the differential dropout rates among male and female students in the Hebrew University Medical School. The base rate was varied in (c) by partitioning the population into males vs. females; siblings vs. only children; or people with a history of depression vs. "normal" people. The likelihood ratio was presented as 9 in the depressives vs. "normals" case (denoted Problem 2').

The 14 problems produced by these variations did not form a factorial design, as different problems incorporated different numbers of the listed variations. In all, they were

presented to some 600 subjects. The modal response was 75% throughout (90% in Problem 2'). It was given by between 25% and 80% of the respondents. The median response was 75% in ten of the problems, 70% in three, and 80% in Problem 2'.

Interestingly, Problem 2 is subject to a slight reformulation which normatively makes the base rates irrelevant. Just read "the number of suicides is three times larger among single people than among married people" for "the percentage ...". That subjects were not merely careless in reading the problem is shown by the similarity of their response pattern when the suicide percentages were stated explicitly. In general, "carelessness" explanations of the base-rate fallacy should not be pushed too far unless the same, or highly similar, confusions can account for all the results. Finding an ad hoc reformulation is too much like finding a question to fit the answer.

2.4 Can People Integrate Uncertainties?

In light of our results so far, one might doubt that people are capable of combining uncertainty from two sources. To test this possibility, consider the following problem.

> Problem 3: Two cab companies operate in a given city, the Blue and the Green (according to the color of the cab they run). 85% of the cabs in the city are Blue, and 15% are Green.
>
> A cab was involved in a hit-and-run accident at night. There were two witnesses to the accident. One claimed that the errant cab had been Green, and the other claimed that it had been Blue.

The court tested the witnesses' ability to distinguish between Blue and Green cabs under nighttime visibility conditions. It found the first witness (Green) able to identify the correct color about 80% of the time, confusing it with the other color 20% of the time; the second witness (Blue) identified each color correctly 70% of the time, and erred about 30% of the time. What do you think are the chances that the errant cab was Green, as the first witness claimed?

Of 27 subjects responding to Problem 3, 14 gave an assessment of 55% (midway between the assessments implied by each witness alone, disregarding base rates), and all but one gave assessments between 50% and 60%.

In Problem 3' (not reproduced in this text) both witnesses identified the cab as Green. Twenty-four of the 29 subjects answering this problem gave an assessment of 75% -- again, midway between the two witness-based assessments. While still disregarding the base rates, our subjects appear to be averaging the probabilistic implications of the two testimonies. Although averaging is not the proper way to calculate the joint impact of the two independent testimonies (which is to reapply Bayes' rule), it clearly indicates that both sources are considered. (For an extended normative discussion, see Tversky & Kahneman, in press). Two symmetrical sources of uncertainty can be dealt with simultaneously.

What if both items are base rates?

Problem 4: Consider the following statistics regarding students of the School of Social Sciences at the Hebrew University. 80% of the doctoral students in this

school are male. 70% of the students in the Department of Sociology are female.

> X is a doctoral student in the Department of Sociology (within the School of Social Sciences). What do you think are the chances that X is male?

Figure 2-3 displays the distribution of responses given by 117 subjects to this problem. The pattern of results here is somewhat different than that of Problem 3, its dual counterpart, particularly in that about 40% of the respondents based their estimate on one item only. Note, however, that no one item dominated the other; in fact, subjects were equally divided between them. But then, Problem 3 itself differs from Problem 2 in two important respects: (a) the information given in Problem 4 is insufficient to *determine a unique* correct response. In the absence of data or assumptions regarding the joint distribution of the two variables, any response is permissible -- including 30% and 80%, the modal responses; this is not true with Problem 3; (b) the two base rates don't appear intuitively as equivalent as the two witnesses in Problem 3. Apparently, some subjects considered field of studies more important than degree sought, and others vice versa. In short, the results here are less clear cut than in Problem 3, but it is encouraging to note that the median response is 55% (midway between the two base rates), and no one base rate enjoyed a clear superiority.

2.5 Why are Base Rates Ignored?

The problems discussed so far both demonstrate the generality of the base-rate fallacy, and exclude some possible

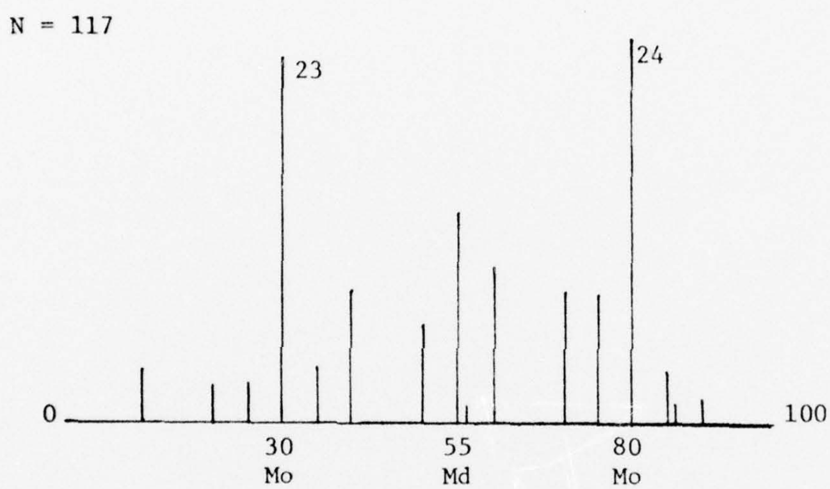

FIGURE 2-3. DISTRIBUTION OF RESPONSES TO DOUBLE BASE RATE PROBLEM 4

explanations for it. We have seen the failure of earlier proposals, Kahneman and Tversky's representativeness, and Nisbett and Borgida's saliency. We have seen that the effect is not an artifact of the elicitation method (e.g., item order). It clearly goes beyond simple misreading of the problem. It cannot be attributed to inherent inability to integrate two sources of uncertainty. Base rates are apparently ignored because subjects feel they <u>should</u> be ignored. To put it plainly, they seem irrelevant.

It is important to note that base rates do not always seem irrelevant. In fact, when they are the only information available, they are clearly utilized (Kahneman & Tversky, 1973; Lyon & Slovic, 1976; Bar-Hillel, Note 1). It is only in the presence of additional information that base rates are ignored.

A possible account for this phenomenon is as follows: people order information by its perceived degree of relevance to the problem they are judging. If two items seem equally relevant, they will both play a role in determining the final estimate. But if one is seen as more relevant than the other, the former will dominate the latter in people's judgments. It needs to be pointed out that these judgments of relevance levels are independent of quantitative considerations, i.e., an item of no diagnostic value may nevertheless be judged more relevant than an item of high diagnosticity. Judged diagnosticity will affect the weights assigned to different items only <u>within</u> levels. The levels themselves are crude, almost qualitative, categories.

This paper does not offer a theory of (subjective) relevance. Indeed, our subjects never made direct relevance judgments. Rather, it suggests some item characteristics which

seem intuitively to affect perceived relevance and the reader is encouraged to assess the plausibility of the account by his own intuition.

One suggestion is that case-specific information is typically judged as more relevant than general considerations. In Kahneman and Tversky's (1973) experiments, the case-specific information was labeled "individuating", since it actually described the target case. In Cab Problem 1, the indicant information is case specific in the sense that the witness is testifying as to the color of the very cab that was involved in the accident. While it is fallacious to ignore base rates in these problems, specific information often does justifiably dominate more general information. For example, predicting life expectancy for a random newborn improves when the infant's sex or weight is known.

The suicide problem (2) differs in that it offers two items of information which are both population statistics. Why does one nevertheless dominate the other? This brings us to a second suggestion: Data which are interpreted as relating causally to the target event are judged as more relevant than data which are seen as "mere statistics". The fact that more young adults are married than single is not perceived as causally related to suicide, but the difference in the suicide rates of these two groups readily implies a greater propensity on the part of single individuals to commit suicide than on the part of married individuals. Ajzen (Note 3) suggests a similar "causality heuristic", claiming that "people rely on information perceived to have a causal relation to the criterion, while disregarding valid but noncausal information". (p. 1). He demonstrated, as we do below, that base rates which are made

to appear causally related to the target outcome do, in fact, assume a role in people's predictions. A similar idea is expressed in Tversky and Kahneman (in press).

The idea of relevance ranking is more powerful than either specificity or causality, since it can account for the fact that the same information (e.g., base rate) may be used in one context but ignored in another, depending on the informational "competition".

We proceed now to review some experiments designed to test one implication or another of this relevance ranking account.

2.6 The Dream Problem

Although imposing a differential base rate on an existing dichotomy (as in Suicide Problem 2) is a powerful way of inducing a causal interpretation of data, other ways exist, as seen in problem 5.

> Problem 5: Studies of dreaming have shown that 80% of adults of both sexes report that they dream, if only occasionally, whereas 20% claim they do not remember ever dreaming. Accordingly, people are classified by dream investigators as "Dreamers" or "Nondreamers". In close to 70% of all married couples, husband and wife share the same classification, i.e., both are Dreamers or both are Nondreamers, whereas slightly more than 30% of couples are made up of one Dreamer and one Nondreamer.

> Mrs. X is a Nondreamer. What do you think are the chances that her husband is also a Nondreamer?

In this problem, two base rates are offered, that of dreaming for individuals, and that of matching for married couples. The target case is a married individual, so both base rates apply to him. Ostensibly, the two items play analogous roles. Undoubtedly, if either were given alone, it would have determined the majority of responses. In fact, however, there is a marked assymetry between the two items, from both a formal and a psychological point of view. Formally speaking, what the data tell us is that mating is random. We expect 64% of couples (.80 x .80) to be both Dreamers, and 4% (.20 x .20) to be both Nondreamers, for a total of 68% (i.e., "close to 70%"). Either base rate is equivalent to random mating, given the other base rate. Thus a spouse's classification is entirely irrelevant -- assessments should be based on the dreaming base rate alone. Psychologically speaking, the data seem to tell the converse story. Never mind the individual base rate for dreaming -- when people marry they tend to find similarly classified mates. For a married target case, therefore, the base rate for matching among couples should predominate. That this is indeed so can be seen in Figure 2-4.

Two additional versions of Problem 5 were presented to 52 and 49 subjects, respectively. In the first version, the spouse's classification was given as Dreamer. In the second version, item order was reversed. The same median and mode of 70% were obtained.

As further evidence that subjects interpret the 70% proportion of matches as reflecting a tendency for individuals

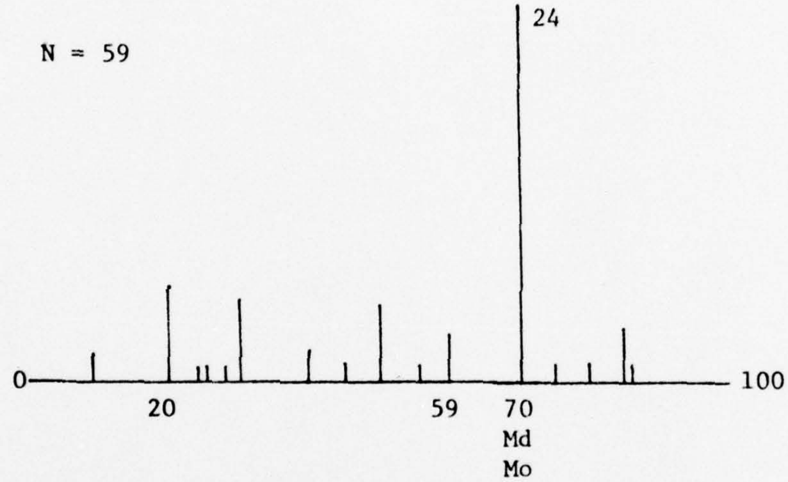

FIGURE 2-4. DISTRIBUTION OF RESPONSES TO DREAM PROBLEM 5

to marry alike, subjects were given yet another version of Problem 5. It had the same opening paragraph, but then went on to say:

> Problem 5': ...with respect to dreaming, mating is completely random.
>
> Mrs. X is a Nondreamer. What do you think are the chances that her husband is also a Nondreamer?

Some other formulations were: "the classification of husband and wife was found to be independent" and "the spouse's classification was found to have no predictive validity". The cover story was also changed, to couples of mother-daughter (rather than husband-wife). A total of 270 subjects saw some version of Problem 5'. The median response was always 50%. The modal response was 50% in five questions, and 20% in two others. Naturally, if people believe that 50% is the expected number of matched pairs under conditions of random mating, it is no wonder that they interpret 70% matched couples as indicating a tendency to marry alike. The base-rate fallacy is not limited to Bayesian inferences.

2.7 Assimilating Base Rates and Indicators

One implication of our proposed account is that by making base rates and indicators seem equally relevant to the target case, the dominance of one by the other would give way to some form of joint influence. We now describe some attempts to do just that.

Problem 6: A large water-pumping facility is operated simultaneously by two giant motors. The motors are virtually identical (in terms of model, age, etc.), except that a long history of breakdowns in the facility has shown that one motor, call it A, was responsible for 85% of the breakdowns, whereas the other, B, caused 15% of the breakdowns only.

To mend a motor, it must be idled and taken apart, an expensive and drawn out affair. Therefore, several tests are usually done to get some prior notion which motor to tackle. One of these tests employs a mechanical device which operates, roughly, by pointing at the motor whose magnetic field is weaker. In 4 cases out of 5, a faulty motor creates a weaker field, but in 1 case out of 5 this effect may be accidentally caused.

> Suppose a breakdown has just occurred. The device is pointed at motor B.[4] What do you think are the chances that motor B is responsible for this breakdown?

As in the Cab Problem 1 and other instances of imperfect diagnosis, we have here a device that singles out a specific motor as the likely cause of a mechanical failure. However, the present base rate is readily interpreted as an individual attribute of the two motors, implying that one motor, A is in worse shape than the other. Thus, both the base rate and indicator single out a specific suspect.[5]

As can be seen in Figure 2-5, the pattern of results given by 39 subjects to this question is similar to that

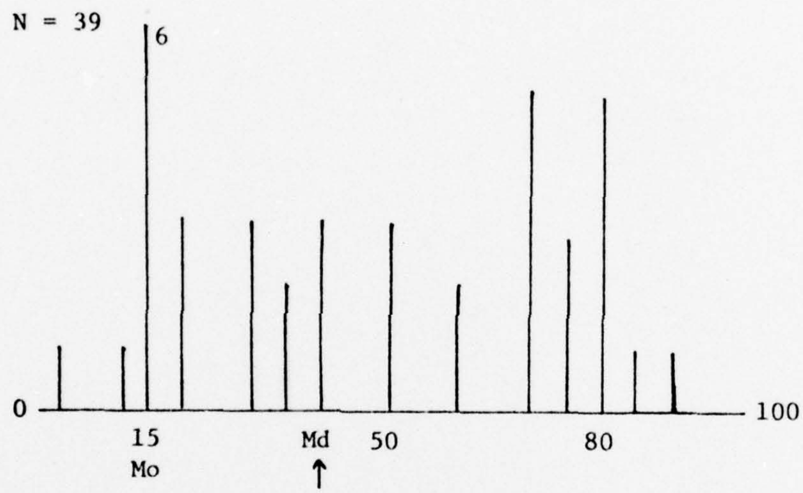

FIGURE 2-5. DISTRIBUTION OF RESPONSES TO MOTOR PROBLEM 6

obtained in Problems 3 and 4. There is no prevailing strategy and, correspondingly, no assessment favored by a large proportion of subjects, producing the diversity of responses characteristic of problems in which the base-rate fallacy is not manifest. However, over 60% of the subjects gave assessments interpretable as weighted averages of the two items of information (i.e., they lie strictly between 15% and 80%, the assessments corresponding to the individual items), and the median of the distribution is at 40%, remarkably close to the correct Bayesian posterior of 41%.

In the following problem, the strategy for assimilating base rates and indicators was reversed.

> Problem 7: Two cab companies operate in a given city, the Blue and the Green (according to the color of cab they run). Eighty-five percent of the cabs in the city are Blue, and 15% are Green. A cab was involved in a hit-and-run accident at night, in which a pedestrian was run down. The wounded pedestrian later testified that though he did not see the color of the cab, due to the bad visibility conditions that night, he remembers hearing the sound of an intercom coming through the cab window. The police investigation discovered that intercoms are installed in 80% of the Green cabs, and in 20% of the Blue cabs.
>
> What do you think are the chances that the errant cab was Green?

Figure 2-6 shows the distribution of 35 subjects' responses to this problem. Here an attribute was chosen which

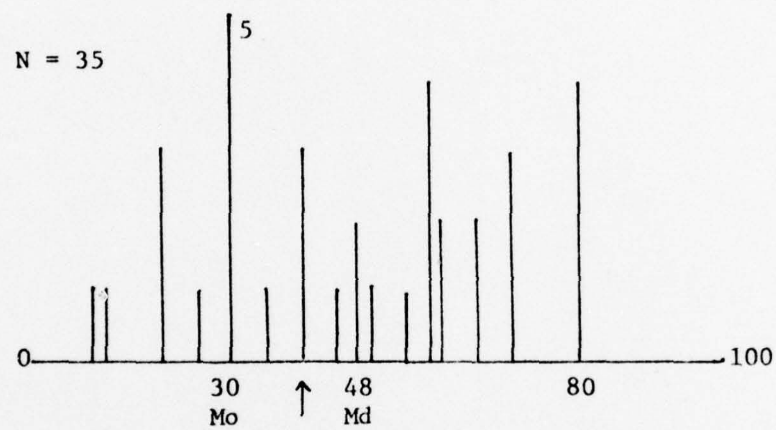

FIGURE 2-6. DISTRIBUTION OF RESPONSES TO INTERCOM PROBLEM 7

though nonuniformly distributed between the two population subclasses, is hard to conceive of causally. It is more naturally thought of as mere statistical coincidence, much in the manner in which base rates are typically construed. The median response is 48%, close to the correct 41%. We again encounter a somewhat flat distribution, with no one prevalent response.

Thus, either by increasing the relevance of base rates to indicator level, or decreasing the relevance of indicators to base-rate level, the two can be caused to combine.

Problem 6 was one of five problems run in this study in which base rates were applied to individual cases. They all used the same parameters and format of presentation, and differed in cover story only. Likewise, Problem 7 is one of two problems employed. The following table summarizes the results of all seven variants. Problems 6 and 7 of the text appear, respectively, as 6A and 7B in Table 2-1.

TABLE 2-1. RESULTS FOR PROBLEMS 6 & 7, AND THEIR VARIATIONS

	Problem 6					Problem 7		
Problem	A	B	C	D	E	A	B	Overall
No. of Ss	39	46	28	67	39	35	23	220
Median Assessments	40	60	38	68	75	48	42	60
Modal Assessments (No. of Ss)	15(16)	80(8)	20(7)	80(18)	80(11)	30(5)	42,80(4)	80(44)

3. DISCUSSION

3.1 Further Directions For Research

A series of seven problems are presented in detail in this paper, drawn from a larger pool of 45 problems. The problems are presented in a sequence that reflects the historical development of the study: attempts to establish the robustness of the base rate fallacy, followed by a search for a "pure" example which would be impervious to some possible accounts of the fallacy, this in turn leading to the emergence of the account this paper propounds, and culminating in some examples, tailored by the implications of this account, which demonstrate how base rates can influence subjective probabilities.

The problems studied can be roughly divided into two groups. The first group contains problems in which one item dominated another (1, 4, 5). These problems are characterized by a relatively high degree of consensus among subjects, with responses converging on the indicator-implied estimate. The problems in the second group, on the other hand (2, 3, 6 and 7), yielded flatter, less elegant distributions, with two or more modes (Problem 2 is an exception). They are more aptly described as having no apparent dominance rather than as problems in which a well defined integration policy emerged. This latter group represents an exercise in designing questions which would induce subjects to interpret particular data in ways that make them appear more or less relevant. The study offers neither a systematic theory of judged relevance, nor any predictions as to how items which are equally relevant, but not necessarily equally diagnostic, would be combined. These gaps indicate directions for future research, with a more systematic set of problem types.

Another fascinating research avenue, albeit formal rather than empirical, is in analyzing the normative way of combining uncertainties. Bayes' theorem provides a model for integration in some, but not all, conditions. There are intriguing problems surrounding both the issue of specificity and the issue of causality. For example, if you knew the base rate of Blue cabs in the quarter of town in which the accident occurred, it seems legitimate to substitute that for the base rate of Blue cabs the city over. But if the more specific base rate is only an estimate, the overall base rate cannot be discarded. As to causality, if your statistics show that the presence of a diagnostic cue implies a certain state with a certain probability, the base rate for that state becomes immaterial when the cue is present. But if all you know is the probability with which the state implies the cue, the base rate of the state remains crucial even in the presence of the cue.

Furthermore, there is a question as to how two uncertainties should be combined when both are relevant. If each of two items points to a certain outcome with a certain probability, should their combined impact lead to an estimate which is some average of the two, or should it be more extreme than either individual estimate? How is this affected by priors? By lack of conditional independence of the two estimators? (See a discussion of some of these issues in Tversky & Kahneman, 1976, in press.)

3.2 Other Views of Information Integration

Two major schools have made extensive studies of information processing in Bayesian inference tasks: the Bayesian approach (Slovic & Lichtenstein, 1971) and integration theory (Anderson, 1972). This study is at variance with one central concept of each.

The Bayesian approach: a major finding is that people are conservative probability revisers, i.e., when asked to judge which of two binomial populations is more likely to have yielded a given sample, they almost invariably give estimates which are less extreme than indicated by Bayes' rule. Nonetheless, for a long time many researchers were content to conclude that "the subjects' revision rule is essentially Bayes' theorem" (Beach, 1966, p. 6; see also Edwards, 1968; Peterson & Beach, 1967; Schum & Martin, 1968). Around 1972, the Bayesian approach came under attack from two directions: integration theory, and the judgment-heuristics approach of Kahneman and Tversky. Kahneman and Tversky (1972a) claimed that the Bayesian model failed to capture the most essential determinants of the judgmental process it purported to describe, and that subjects, rather than being conservative Bayesians, were in fact not Bayesian at all. By choosing tasks carefully, Kahneman and Tversky showed that people's estimates in Bayesian tasks need not even be monotonically related to the true Bayesian estimates. However, since they used the same type of task in their study, numerically speaking they too obtained conservative assessments of data diagnosticity. In contrast, studies of the base-rate fallacy readily yield radical results, i.e., probability revisions more extreme than allowed by Bayes' rule. In fact, by controlling the diagnosticity of the indicator (whether explicitly, as in the cab problem, or implicitly as in the Kahneman and Tversky 1973 studies) vis a vis the base rate, one can achieve conservatism or radicalism at will. Thus "conservatism" not only isn't a property of people's probability revisions, it isn't even a property of their judgments of diagnosticity. The whole finding is a fluke of the paradigm used by the Bayesian approach. Conservatism is a "non effect" (Anderson, 1972).

The integration theory approach: a basic assumption of information-integration theory, the most unified and comprehensive approach embodying the "time honored...conception of the organism as an integrator of stimulus information...in judgment" (Anderson, 1972, p. 3) is that of a series of stimuli each has relevance for a particular judgmental task, then the combined effect of the series upon the response can be described by a model which assigns each valued stimulus an appropriate (subjective) weight, roughly corresponding to its impact upon the response. Typically, an additional assumption of independence is introduced, according to which the weight (though, of course, not necessarily the <u>relative</u> weight) of a stimulus is independent of the other stimuli with which it is combined. Integration theory has been applied to a variety of judgmental tasks, including the Bayesian inference tasks discussed above. Shanteau (1970, 1972) compared the integration theory and the Bayesian approach to these tasks, and concluded that integration theory gives a superior account of subjects' behavior.

In one study, Shanteau and Anderson (1972) found that when judging the value of diagnostic information in a task in which subjects had an initial probability P of winning a sum of money, they were willing to pay more for an item of fixed diagnosticity the lower P was, thereby indicating a sensitivity of sorts to prior probabilities even under conditions of constant diagnosticity. This result seems incompatible with the base-rate fallacy. However, upon closer examination of Shanteau and Anderson's tasks, this appears not to be the case. While their subjects were willing to pay more for an indicator when it was more needed, i.e., when the initial probability of success is lower, they seemed unaware that they were in some cases paying for a worthless commodity, namely for information which should have in no way

affected their response. In other words, subjects were willing to pay more for more diagnostic information, even when this additional diagnosticity when combined with the prior should have had no impact on their guessing strategy. Had subjects been asked to evaluate posterior probabilities in this situation, I suggest that their posterior estimates would have manifested the same insensitivity to priors typical to our subjects. Some support for this position is given indirectly by the following data, gathered in a kind of "thought experiment" modelled after Edwards (1968).[6] Fifty-four subjects were given the following problem:

> Imagine ten urns full of red and blue beads. Eight of these urns contain a majority of blue beads, and will be referred to hereafter as the Blue urns. The other two urns contain a majority of red beads, and will be referred to hereafter as the Red urns. The proportion of the majority color in each urn is 75%. Suppose someone first selects an urn on a random basis, and then blindly draws four beads from the urn. Three of the beads turn out to be blue, and one red.
>
> What do you think is the probability that the beads were drawn from a Blue urn?

In other versions of this question, the number of Blue urns was given as five out of the total ten, and/or the number of blue beads in the sample was given as one. Results are presented in Table 3-1.

The appearance of identical modal estimates in the first two rows and in the second two rows reflects insensitivity to priors, i.e., the base-rate fallacy. The complementation of the

TABLE 3-1. SUMMARY OF BAYESIAN THOUGHT EXPERIMENT

Problem Description				Results		
Number	Urns	Sample	Normative Bayesian Assessment	Modal Assessment	Freq. of Modal Assessment	No. of Subjects
1	8B 2R	3B 1R	.97B	.75B	14	54
2	5B 5R	3B 1R	.90B	.75B	20	50
3	8B 2R	1B 3R	.31B	.25B	13	53
4	5B 5R	1B 3R	.10B	.25B	6	20

modal assessments in rows 1 and 3 and in rows 2 and 4 can be seen as a replication and support of Kahneman and Tversky's claim that people judge diagnosticity via representativeness. Incidentaly, note that in row 3 we have a case of "radicalism" rather than conservatism. Clearly, no integration model can account for these results.

One striking result of the present study, which would be difficult to handle within integration theory, is the fact that precisely the same item of information (e.g., the base rate of Blue cabs) is treated differently when coupled with a more relevant additional item (e.g., the witness' testimony) and when coupled with an equally relevant item (e.g., the intercom distribution) -- in spite of both additional items being formally equivalent. In other words, we have here a very strong context effect, wherein the weight assigned to one item depends very clearly on the <u>nature</u> of the item with which it is coupled. Knowing the isolated impact of two individual items on subjects' judgments does not allow us to predict their weights in combination. Once the weight of an item depends not only on algebraic considerations but on the way its relationship to the criterion is interpreted (with this interpretation being open to external manipulation), the integration theory approach here receives a distinctly ad hoc flavor.

Psychologists are familiar with the fact that as information is added in a probabilistic inference task, confidence increases rapidly, whereas accuracy increases only minimally (Oskamp, 1965), if at all. This study shows that new information may actually lead to a decline in predictive performance, by suppressing existing information of greater predictive validity. In the mind of the human judge, more is not always superior to less.

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6. FOOTNOTES

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[1]Ninety-five additional subjects were run by Kahneman & Tversky (1972b) and by Lyon & Slovic (1976).

[2]It is interesting to note that only under conditions of equal base rates does the claim that each color has an equal chance of being identified properly entail the claim that each color attribution has an equal chance of turning out to be correct. Whereas the former tells us only that the witness' perceptions are unbiased, any realization of the latter would call for a very complex system of response biases on the part of the witness, varying with the population base rate. It is for this reason, of course, that the diagnosticity of indicators is typically stated in terms of their Hit and correct-Reject rates, rather than in terms of their efficiency as Meehl and Rosen would have it. It is the former, but not the latter, which, being a constant feature of the indicator, remains invariant under fluctuating base rates, costs, etc.

[3]According to the Israel Bureau of Statistics, 85% of the 25-35 age group in Israel (where this study was run) are married. However, since subjects estimate this proportion as 80% (median and modal response of 32 Ss, with an interquartile range of 70%-80%), we used a proportion conforming to their guess.

[4]The situation described in this question, as in all others, is strictly fictional. However, an attempt was made at credibility throughout.

[5]One could argue that the affect achieved here is linking the base rates causally to breakdowns, rather than making it case specific. Possibly both happen, and either is compatible with the hypothesis studied.

[6]The idea for modelling a thought experiment after Edwards was suggested to me by Lyon's (1973, Note 4) unpublished master's thesis. I refer to it as a "thought experiment" since in the original Edwards study, the assessments were made on real urns, beads, and samples.

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The base-rate fallacy is people's tendency to ignore base rates in favor of case-specific information (when such is available), rather than integrate the two. This tendency has important implications for understanding judgment phenomena in many clinical, legal, and social-psychological settings. According to the account suggested in this paper, people order information by its perceived degree of relevance, and let high-relevance items dominate low-relevance items. Information that relates

more specifically to the judged target case or is causally linked to it is deemed more relevant than general background data, thus yielding the base-rate fallacy in typical Bayesian inference problems. A large series of probabilistic inference problems was presented to subjects, in which relevance was manipulated in various ways, and the empirical results confirm the above account. In particular, base rates will be combined with other information when the two kinds of information are made to appear equally relevant.